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A Synergistic Approach for Maximizing Human-Automation System Performance
Project No. 7000

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A SYNERGISTIC APPROACH FOR MAXIMIZING HUMAN-AUTOMATION SYSTEM PERFORMANCE (HUMANS)
DFY 06 Year-End Report
IR&D Project No. 7000, ACCOUNT#18000
Ayanna Howard (Georgia Institute of Technology)

DESCRIPTION OF PROJECT

To develop a robust method for autonomous planning of system activities, we proposed a predictive modeling and assessment tool for human-automation system performance (HumAnS). HumAnS is capable of estimating the effects of various workloads on human performance in real-time and determining the performance tradeoffs derived from task allocation between humans and robotic systems.

HumAnS uses a systematic approach to predict the effects of various workloads on human and robotic system performance and allocates tasks accordingly to maximize mission success. The approach can be applied to a wide range of human-automation activities performed in complex environments and consists of three primary steps:

1) Scenario Decomposition: decompose scenario into set of major functional task primitives and define performance metrics for each primitive
2) Performance Evaluation: evaluate the performance of all agents (human, robot) in performing each task primitive and compute composite task scores to enable trade-off studies to be made for allocation of tasks between humans and robots.
3) Performance Prediction: develop an optimization model to determine optimal task allocation between human and robotic-system by evaluating different combinations of task primitives implemented by each agent that maximize the composite task score

PROBLEM

One of the key issues in human-robot interaction scenarios is determining which tasks are best done with humans, or robotic systems, or a combination of each. In this case, we define human-robot interaction scenarios as any situation in which a human operator can apply control to an automated system having a physical embodiment, which is not co-located in the same space as the human. Thus human-robot interaction scenarios include systems consisting of unmanned aerial vehicles, autonomous underwater vehicles, rovers, etc. As these human-robotic systems are increasingly deployed in various applications such as space exploration missions, shuttle rendezvous and docking, tele-surgery, and military applications, there is a corresponding need to develop methods that optimally partition the task space to ensure mission success. The process of selecting an appropriate technique for evaluation of human-robotic systems typically though requires knowledge of the objectives of a task and a realistic environment in which to assess performance. In addition, assessment of systems having both human and robotic agents must focus on the capability of both agents. If the human operator is overloaded, but the human agent is still required to perform during a crisis, the system should be capable of evaluating performance accordingly and allow the redistribution of tasks such that the human can deal with the high-threat task, while the robotic system tries to manage the more repetitive workload. Although research in human-robot performance assessment is expanding, an approach that integrates the contributions of both human and robot agents and compares the performance of teams of agents has been only limitedly addressed. The developed HumAnS system addresses these limitations and uses methods to predict the effects of various workloads on both human and machine performance and allocates task accordingly between human and automated systems to maximize performance.

OBJECTIVES

The proposed HumAnS system addresses existing limitations in evaluating hybrid human-robotic systems. HumAnS uses methods to predict the effects of various workloads on both human and machine performance and allocates task accordingly between human and robotic systems to maximize performance.

The overall objectives is to develop a real-time assessment and prediction system for determining optimal task allocation between human and machine based on the following objectives:

- Objective (1): Identify the space of human-automation tasks for space mission scenarios and define an inclusive set of functional primitives/operations.
- Objective (2): Determine agent performance metrics associated with functional operations.
- Objective (3): Develop an optimization model to determine optimal task allocation between human and automated-system.

PROGRESS

In the current year, we have focused on refining and improving our previous assessment and prediction methodology to improve performance for human-robot mission scenarios based on implementation of the following tasks:

1) Generalizing and Refining Performance Metrics - Construct performance evaluation function for human-robot systems by learning performance criteria via human input data
2) On-line Learning of Scenario Decomposition - Develop an on-line learning system capable of decomposing new mission scenarios into individual tasks through interaction
3) On-line Learning for Refinement of Scenario Decomposition - During actual operation of the human-automated system, allow refinement of the estimated scenario decomposition in real time

	MONTH											
	1	2	3	4	5	6	7	8	9	10	11	12
Develop generalized evaluation function and integrate accuracy metric into determination of agent performance												
Midterm Meeting at Draper												
Develop on-line learning methodology to refine estimated performance metrics for current scenario												
Develop on-line learning methodology to decompose a scenario in real-time by identifying task primitives during operations												
Compile final report												
Final Meeting at Draper												

Generalizing and Refining Performance Metrics

The current rendition of the performance evaluation component uses execution time as the primary measure of performance. Other factors, well documented, include accuracy (i.e. how close does the system approach a desired goal position), reliability (i.e. how often can the system reach the same goal with the same accuracy consistently), and success (i.e. how reliably can the system complete a given task). Different methods are used to calculate these parameters, with the most common defined with distance measures, probabilities of error, and confidence factors. In order to allow the prediction system to incorporate the diverse set of metrics used to evaluate agent performance, we have instituted a process in which the automated system learns the performance evaluation function directly from the human operator.

For learning the performance evaluation function, a robot subordinate selects the best task corresponding to the highest reward. It is the role of the human operator therefore to provide rewards that correspondingly guide the robot to a desired goal solution. A technique to facilitate selection of correct robot behavior is genetic, or evolutionary, algorithms. Genetic algorithms are an adaptive method in which a search is performed to find a set of behaviors that maximize an objective function. In human-robot interaction scenarios, the objective function can be defined by the human operator in order to guide the robot to the desired goal solution based on desired performance.

To model this interaction within the domain of human-robot interaction, an action-reward structure must be provided that is built upon a lower level communication scheme. Using a traditional genetic algorithm would imply an action-reward behavior, but communication between the human user and the robotic agent would be minimal. In traditional genetic algorithms, a user would provide a fitness function and the algorithm, after several generations, would develop solutions to maximize fitness according to the provided fitness function. Though this may be perceived as an action-reward type interaction, its rigid nature leads it away from being a good model for learning the performance evaluation function. Hence, our proposed solution is a genetic algorithm whose fitness function varies in real time and in accordance with a human operator's desires. This avoids reprogramming fitness functions whenever the human operator desires to attain a solution in an unforeseen manner.

In our application, a fitness function for finding an optimal solution is built on a combination of N functions. During the initialization stage, each function is weighted equally to determine fitness. Through operator use of the HumAnS-3D interface (Figure 1), however, these weights are altered as a function of user feedback. The concept is that user preference allows the fitness standard to be dynamically allocated in real time.

For implementation, the system runs through iterations of the genetic algorithm, and displays the five highest ranked paths to the user. The user then selects what they consider their top two choices. The associated chromosomes are then reinserted into a completely new gene pool of a new instance of the genetic algorithm. Hence, on the next run, convergence occurs at a faster rate and an optimization function based on the statically weighted fitness function is designed. By introducing this human-in-the-loop implementation, the user, in essence, acts as the dynamic portion of the fitness standard. This allows us to have a generalized performance function that can be learned by the automated system.

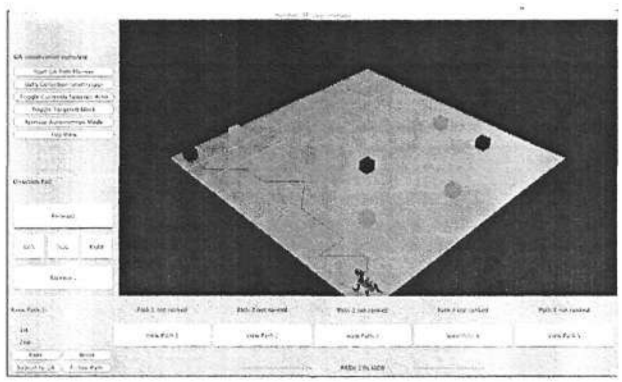

Figure 1. HumAnS-3D environment for learning of performance evaluation function

On-line Learning of Scenario Decomposition

With the ultimate goal of operations in space by a team comprised of humans and robots, the second milestone entailed an on-line learning of scenario decomposition. A scenario implemented by a human is comprised of a set of basic tasks, known as task primitives, which can be emulated by a robot. An initial list of task primitives were first modeled and required inputs and outputs were identified (as shown in the table below). In addition, the various characteristics that can be used to map the human tele-operation input data into the task primitive inputs and outputs were classified. After identifying task start and end points that can be used to classify known task primitives, an approach was developed to add new task primitives. This algorithm identified the new tasks start and end points, isolated the backgrounds and objects, and mapped changes to I/O configurations that occurred during task implementation. An 'Ask for Help' task primitive was introduced to ensure that if the robot is unable to identify or complete certain routines, it is able to obtain the required information from the control center when needed.

Task	Start	End
Grasp	Clicking and holding left mouse button object	Releasing button
Release	Releasing button	None
Identify	Clicking left mouse button on object	Releasing button
Lift	Double clicking on object	Releasing button
Unload	Double clicking on object	Releasing button
Locate/Localize	No motion for 5 sec (input = object name)	Move pointer away
Mate	Clicking and holding right mouse button object	Releasing button
Unmate	Releasing button	None
Model/Represent	No motion for 5 sec (input = everything)	None
Plan	No motion for 5 sec (input = everything)	None
Track	Click of right mouse button	Releasing button
Traverse	Clicking and holding left mouse button on robot	Releasing button
Ask for help	None	None

Task hierarchies were then constructed for three possible scenarios: A robot assisting an injured astronaut, a robot performing sample collection, and a robot paving a path. These hierarchies consisted of identified task primitives and the various inputs and outputs required for each stage and how they are interlinked. Using this construct, we were able to test interaction with multiple roots such that a new scenario could be learned and used to control any of N remote agents (Figure 2).

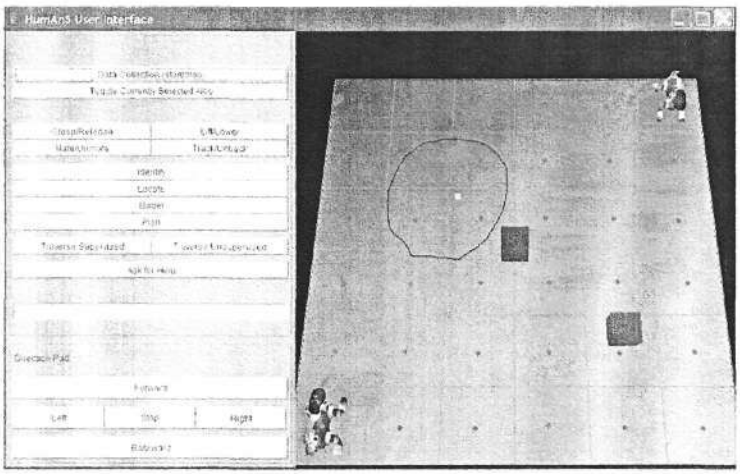

Figure 2. HumAnS-3D Environment for on-line learning of scenarios

On-line Learning for Refinement of Scenario Decomposition

For on-line refinement of scenario decompositions, a language parser for robot interaction that acts as a limited natural language processor was developed. The goal was to take a human provided linguistic sentence, provided in the form of a command, and decompose it into a set of sequential task primitives, which the robot could execute. The parser takes as input a sentence and outputs a series of task primitives that the robot can execute. The task primitives are linked in a way that enables a potential output from an earlier primitive to propagate and be used as input to a later primitive, which is essential for successful implementation.

The software itself recognizes any direct task primitive, such as "Locate rock", but the main intelligence of the software comes in its ability to interpret or infer the existence or necessity of certain primitives in order to be able to execute others. For example, a command of the form "Move the rock to base", would first require the robot to perform a traversal to the rock, mate with it and then traverse to the base. The move to the rock is implicit in the sentence structure. In terms of the software details, this required a new primitive class, which specified details about individual primitives as well as the ability to retrieve, expand and modify certain pieces of information such as its inputs, outputs and the type of inputs and outputs it gives. These were used in a main Parser class, which tokenized a string input and processed it accordingly (Figure 3).

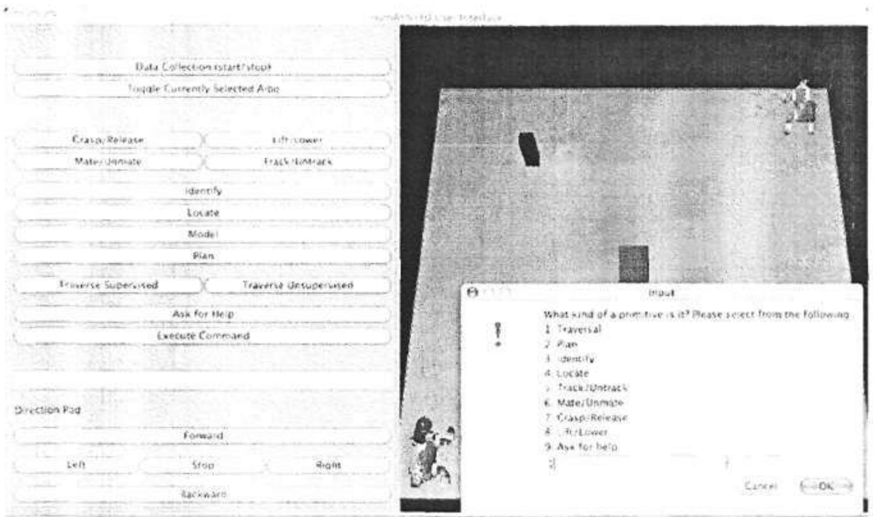

Figure 3. Language parser for refinement of learned scenario

Thus far, we have shown that the current rendition of the HumAnS system is capable of evaluating human-robot interaction systems that incorporate aspects of both human and robotic system performance, i.e. the capability of the robotic system to implement tasks is understood, as well as the human's ability to perform. More technical detail is provided in the papers listed under the reference section.

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